Expanding the Boundaries of Health Informatics Using AI: Papers from the 2014 AAAI Fall Symposium

HowNutsAreTheDutch: Personalized Feedback on a National Scale

Frank Blaauw[1,2], Lian van der Krieke[2], Elske Bos[2], Ando Emerencia[1,2], Bertus F. Jeronimus[2], Maria Schenk[2] Stijn de Vos[2], Rob Wanders[2], Klaas Wardenaar[2], Johanna T. W. Wigman[2], Marco Aiello[1] and Peter de Jonge[2]

[1]Distributed Systems Group, JBI, University of Groningen,
Nijenborg 9, 9747 AG Groningen, The Netherlands
[2]ICPE, University Medical Center Groningen, University of Groningen,
Hanzeplein 1, 9700 RB Groningen, The Netherlands

Abstract

A paradigm shift is taking place in the field of mental healthcare and patient wellbeing. Traditionally, the attempts at sustaining and enhancing wellbeing were mainly based on the comparison of the individual with the population average. Recently, attention has shifted towards a more personal, *idiographic* approach. Such shift calls for new solutions to get data about individuals, create personalized models of wellbeing and translating these into personalized advice.

Idiographic research can be conducted on a large scale by letting people measure themselves. Repeated collection of data, for example by means of questionnaires, provides individuals feedback on and insight into their wellbeing. A way to partially automate this feedback process is by creating software that statistically analyzes, using a method known as vector autoregression, repetitive questionnaire data to determine cause-effect relationships between the measured features. In this paper we describe a means to facilitate these repetitive measurements and to partially automate the feedback process. The paper provides an overview and technical description of such automated analyses software, named Autovar, and its use in an online self-measurement platform.

1 Introduction

Attempts at sustaining and enhancing patient wellbeing are predominantly based on *nomothetic* research (Van der Krieke 2014). In nomothetic research, samples of the population are investigated to find generic laws of patients' wellbeing. These samples are generalized to all individual members of the population that the sample is supposed to be drawn from. As a consequence, the majority of evidence-based treatment guidelines in healthcare apply to a 'non existing average individual' and they do not sufficiently account for the fact that each person is different and should be treated as such (Barlow and Nock 2009).

Recently, researchers have called for a more personal approach in mental healthcare (Molenaar and Campbell 2009), which can be realized by means of (quantitative) *idiographic* research. Idiographic research focuses on within person variation, that is, comparing a person with himself or herself over time. In a typical idiographic study, a person completes multiple, repetitive assessments within a specified time period, resulting into a time series. The collected time series data provides insight into a person's fluctuations in wellbeing over time. Moreover, when the time series data is analyzed with a specific statistical technique, called *vector autoregression*, cause-effect relationships can be revealed between features measured in the repeated assessments. These cause-effect relationships are of particular interest because they allow for prediction, which may pave the way for influencing the cause when the effect is not desirable. Hence, idiographic research and time series assessments can form the basis for a highly personalized treatment advice.

However, health researchers face significant challenges regarding data collection, data analysis and the generation of feedback, when conducting idiographic research and attempting to make the idiographic results available for practice. This has hampered implementation of idiographic research on a large scale.

We hypothesized that the challenges in idiographic research could be tackled by automating part of the data collection, data analysis and feedback generation processes in order to realize a more *personalized medicine*.

In this paper, we present a work in progress of two novel applications, called *HowNutsAreTheDutch* (Dutch: HoeGekIsNL) and *Autovar*, which demonstrate how idiographic research can be conducted on a large scale and how feedback can be generated in the form of personal network diagrams contributing to a personalized medicine. The applications are described consecutively in Section 2 and Section 3. Section 4 provides a basic overview of the application architecture. Section 5 provides a discussion and future directions of the research.

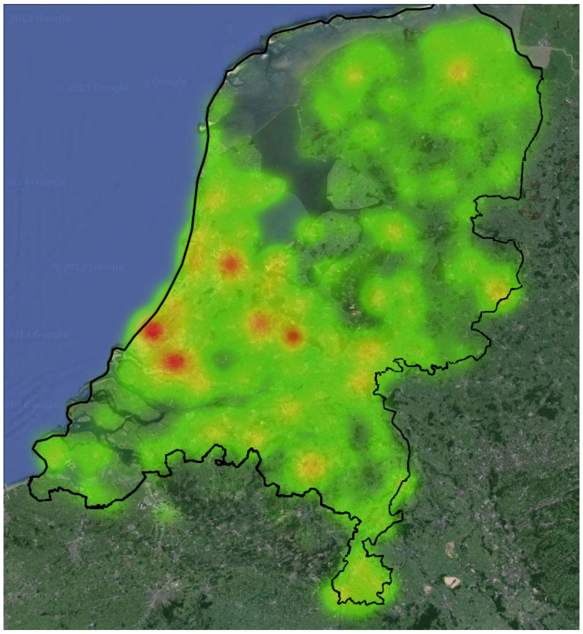

Figure 1: Distribution of the participants in The Netherlands. Light green areas depict a low amount of participants, red areas depict high amounts of participants in that area (the glow outside of the black border are artifacts of the rendering).

2 HowNutsAreTheDutch

HowNutsAreTheDutch is an online platform[1] designed to support self-measurement of mental health for the entire population of The Netherlands. It provides two main parts for self-measurement. The first part consists of several questionnaires that people can complete only once. HowNutsAreTheDutch provides feedback for each of these questionnaires by comparing the individual results to established group results, to provide basic insight in people's mental health. The first version of HowNutsAreTheDutch has been available since mid-December 2013 and has over $11\,000$ participants who completed a total of $52\,000$ questionnaires. Results (up to June 2014) show that the age of the participants ranges from 12 to 82, of which approximately 65% is female. Due to national publicity, the participants are approximately normally distributed throughout The Netherlands, with some peaks around the more crowded areas (in the conurbation of Western Holland) and Groningen (the city in which the research was started), as shown in Figure 1.

The second, more challenging part of HowNutsAreTheDutch, is a diary study consisting of repeated brief questionnaires that people have to complete at fixed time intervals, resulting in a time series dataset. HowNutsAreTheDutch automatically notifies participants when the questionnaires are available. This diary study is a form of idiographic research that allows for highly personalized feedback.

In the HowNutsAreTheDutch diary study, the participants are presented three questionnaires each day; twelve hours before their bedtime, six hours before their bedtime and at their actual bedtime. The study runs for a total of 30 days from the moment the participant started the study. Thus, a person completing the whole study creates a total of 90 measurements (when having no missing measurements). Each of these questionnaires measures several *features*. Each feature represents, for example, an emotion or feeling, such as (but not limited to) gloom, relaxation and worry. The participants can only participate via their mobile phone, since a notification SMS is sent when the questionnaire can be filled out. Besides the practical reasons, using a mobile phone to take measurements is important for the validity of the study. People should have the ability to fill out a questionnaire at all times or wherever they are.

The diary study has been available since the end of May 2014. Approximately 380 people have subscribed to participate (Recorded September 1, 2014). Before the actual study was released, a single person case study was performed for the Dutch magazine *Psychologie Magazine* as a pilot study.

[1] Website: http://www.hoegekis.nl

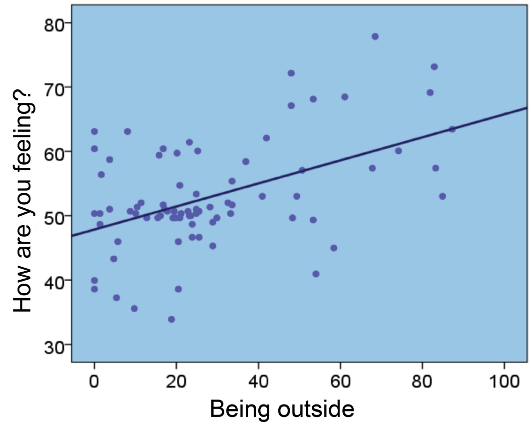

Figure 2: Example scatterplot showing being outside against how someone feels

After completing the diary study, the participants are rewarded with personal feedback. A participant who completes the study with less than 25% missing measurements is rewarded a basic report. This report includes various graphics showing some of the features over time (e.g. relaxation and stress), and general graphics showing, for example, summarized location information of a person during the study. The basic feedback provides insight on the relationships between the measured features and a basic overview of the measurements collected during the study. In our case study the participant received overall feedback on various subjects, such as location, activities and correlational information about the measured features. An example of one of the graphs in the basic feedback is depicted in Figure 2, which shows the correlation between being outside and how well someone feels.

When a person completes the study with less than 15% missing measurements, we provide more in-depth feedback. In this feedback we show how the measured features interact with and cause each other over time. The in-depth feedback is provided by means of an application called Autovar and is presented in the form of network diagrams. Both Autovar and the network diagrams are elaborated in the next section.

3 Autovar

Autovar was developed to automatically analyze time series data, such as the data resulting from the HowNutsAreTheDutch diary study, and generating personal feedback.

3.1 Vector Autoregression

The name Autovar comes from the statistical technique it applies: *vector autoregression* (VAR). This technique has been proposed to analyze time series data because it can reveal cause-effect relationships. VAR was first used in econometric applications (Sargent 1979; Sims 1980), but is now more elaborately used in the field of mental healthcare (Rosmalen et al. 2012; Bringmann et al. 2013; Van der Krieke 2014; Emerencia 2014). The idea behind VAR is that the future values of features can be predicted by analyzing the previous values of features.

For predicting a set of outcome features, VAR uses a combination of *linear regression* and *autoregression* on a vector of predictor features. Both features at the current moment in time, as well as some previous values of all features (including the feature to be predicted), can be used for predicting a future value of a feature. For example, VAR could use measurements based on physical activity, sleep and depressive feelings at time $t = 1$ and at $t = 0$ to help predicting the degree of depressive feelings at $t = 2$ (Rosmalen et al. 2012). VAR analysis encompasses many statistical tests, repetition, and decision moments. Performing a manual VAR analysis of a patient's dataset requires extensive statistical experience and is very time consuming (it may take several days (Van der Krieke 2014)) and is therefore not feasible if many individuals have to be analyzed.

3.2 The Autovar Process

Autovar was created to automate the steps that would otherwise be performed during a manual VAR analysis. In order to find a best model for a dataset, Autovar fits all VAR models within a given combinatorial search space to the data and conducts various statistical tests to see which of the fitted models are valid. In order to find the best model it automatically refines models with a number statistical techniques, for instance removing trends from the data or transforming the data. The implemented steps reflect what a human statistician would do with the data. The resulting models can be used to determine *Granger causal* relationships between the features (Lütkepohl 2005). Granger causal relationships show if values of one variable are useful for predicting the values of another.

A comparison between a (computer-aided) manual VAR analysis and Autovar has been made using a study by Rosmalen et al. (2012). In this study Rosmalen et al. show the ability of predicting both depressive feelings and activity using previous measurements of depressive feelings and activity. Examples of the VAR models used by Rosmalen et al. are provided in Equation (1) and Equation (2). These models show the prediction of *activity* (A) and *depression* (D), by looking at p previous measurements of each value of a feature. In these models, the coefficients (α, β, γ and δ) need to be estimated and ϵ is the prediction error. The outcome values A_t and D_t are the predicted values of respectively the features activity and depression.

$$A_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i A_{t-i} + \sum_{i=1}^{p} \beta_i D_{t-i} + \epsilon_{1t} \tag{1}$$

$$D_t = \beta_0 + \sum_{i=1}^{p} \gamma_i A_{t-i} + \sum_{i=1}^{p} \delta_i D_{t-i} + \epsilon_{2t} \tag{2}$$

The analysis performed by Rosmalen et al. was repeated in Autovar by Van der Krieke et al., with very similar results with regards to model validity, information criteria (which describes how well the selected model fits the data) and Granger causal estimates. Moreover, Autovar and the manual approach of Rosmalen et al. both selected the same model the as being the most applicable (Van der Krieke 2014; Emerencia 2014).

3.3 Network Diagrams

The goal of Autovar is to provide insight into the dynamic relationships between features repetitively measured over time, in an easy to interpret and insightful way. When people provide data on a regular basis, by filling out daily questionnaires as described in Section 2, detailed feedback can be provided with regards to the features one experiences and the way these features interact with each other in the form of a *network diagram*. That is, a diagram showing the relations between the measured features from the dataset. For example, in the study of Rosmalen et al. VAR showed that levels of depression in one person were predicted by previous levels of activity (Rosmalen et al. 2012). Individual insight in these associations enables recognizing personalized targets for intervention to increase or sustain wellbeing. For instance, if a personal network diagram shows that a decrease in depression is preceded by an increase in physical activity, a clinician could advice that person to be more physically active to improve his or her wellbeing.

Figure 3 is one of the network diagrams created using a manual VAR analysis from the data of the case study subject. It depicts how *gloom*, *relaxation*, *worry*, *physical discomfort*, *physical activity* and *living in the moment* interact with and cause each other over time. A plus-sign in the figure depicts a positive relationship in the direction of the arrow (when the feature at the base of the arrow increases, the feature at the tip of the arrow increases next time step). The relationships marked with the minus-sign this relationship is the other way around. The strength of the relationship is shown using the thickness of the arrow.

4 Application architecture

HowNutsAreTheDutch uses two main services to enable the daily measurements and to perform the VAR calculation. The first service is the diary orchestration service (*RoQua*[2]),

[2]Website: http://www.roqua.nl

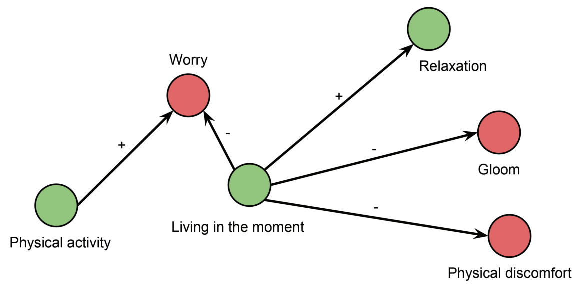

Figure 3: Personal generated feedback, showing the relations between the measured variables.

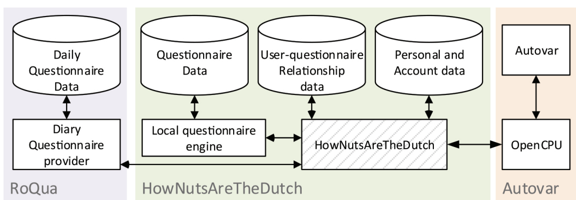

Figure 4: Consise architecture of HowNutsAreTheDutch

which performs scheduling and recording of the daily measurements. RoQua's purpose is to send out notifications to HowNutsAreTheDutch when questionnaires need to be conducted, and to collect the diary data the participants provide. When a participant completes the study (that is, after the 90 days), HowNutsAreTheDutch gathers data from RoQua and forwards it to the second service; the Autovar computation server. Autovar is an application written in the programming language R (a language specialized for statistical computing). Since R does not provide a straightforward way to expose functionality via the internet, Autovar implements a system known as *OpenCPU* (Ooms 2014) to expose the Autovar functionality to HowNutsAreTheDutch. Figure 4 shows a concise deployment diagram of the current situation.

5 Discussion and future directions

No person is the same and no one should be treated as such. In this paper we describe HowNutsAreTheDutch, a platform to provide basic methods to provide participants with personalized feedback about their wellbeing, and Autovar, a means to analyze time series data. Providing personalized advice is important and feasible using these systems.

HowNutsAreTheDutch is an interesting alternative for recording personal mental health data. It provides feedback on diary questionnaire data and could be used as a means to get insight in one's mental state. The novelty of HowNutsAreTheDutch lies in the way the participants are provided with feedback and how this feedback is calculated. To the best of our knowledge, no platform exists which provides the granger causal relations between the measured features, purely based on a participant's own data, and computed using VAR analysis. Although HowNutsAreTheDutch provides an easy to use online platform to perform self-measurement on a large scale, the use of questionnaires could be improved. Filling out questionnaires is a cumbersome job, not to mention three times a day for 30 days. Although filling out questionnaires cannot be automated, it would be interesting if the data could be gathered in a ubiquitous, less cumbersome way, for example, using sensors.

Autovar is a viable solution to effectively allow personal feedback in the field of mental healthcare. It provides meaningful feedback on diary questionnaire data and can be used to create personalized models of wellbeing and to translate these models into personalized advice. Comparisons between the results of Autovar and the results of manual VAR analysis are promising. Although Autovar was mainly developed for mental healthcare data, it could also be used for other time series data.

Autovar needs to be enhanced for both usability and robustness. The feedback currently provided by Autovar is still basic; only Granger causalities in all valid models found by Autovar are shown in a network structure. We plan to create larger network structures, showing dynamicity of feature interaction over time. A study of Bringmann et al. shows possible implementations of a network structure (Bringmann et al. 2013). Autovar's functionality for imputing missing values is still basic and should be improved for robustness. An interesting point of discussion on Autovar is the effect of personalized advice. When Autovar shows that an increase in physical activity predicts a reduction of depression, does an intervention based on increasing activity actually reduce depressive symptoms? To put it differently and more fundamentally, will actual interventions do what Autovar predicts?

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